Modelling Changes To Survey Response Items Over Time In A Britain Financial Literacy Education Study

Abstract

This study develops a general method for modeling changes in response to items relating to students perceptions of personal finance and financial products. The new method is illustrated to analyze data from a sample of 1,250 students aged 16-18 who participated in a financial capability education study in the UK. We demonstrate how a quantitative indicator of the changes in students' responses can be applied in various educational research projects, particularly as a measure of program effectiveness. Predictions are based on prior survey responses, which are taken as relevant historical information for a cohort of students. We find significant changes in the responses of students towards reported career choice following the Financial Literacy Education course at national colleges in the UK.

Keywords: financial capability education, longitudinal study, Monte Carlo, personal finance

Introduction

The UK Government, in its paper "Financial Capability: the Government's Long-Term Approach" set out that "Financial Capability is a broad concept, encompassing the people's knowledge and skills to understand their own financial circumstances, along with the motivation to take action." (FC, 2007, p. 23). Financial literacy and financial capability are terms often used interchangeably (Lord, 2001; Xiao & O'Neill 2016). Financially capable consumers plan ahead, find and use information, know when to seek advice and can understand and act on this advice, leading to greater participation in the financial services market (HMSO, 2007). Atkinson, McKay, Kenmson, and Collard (2006) present financial capability as encompassing four domains: "managing money", "planning ahead", "choosing products" and "staying informed". They note that while some people may be particularly capable in some financial domains, they may score low in others. On the other-hand, Cutler and Devlin (1996) define financial literacy as comprising two main dimensions: financial knowledge and confidence. The aim of financial literacy education is to provide young people support for improving their personal financial practices.

A practical research project—Financial Literacy Education (FLE) was conducted in 2004 in the UK (Davis, et al., 2009). This project examined the impact of a financial studies course on young people's financial capability. In doing so, that project addressed the following questions:

1. How do students' participate in personal financial management?
2. How do students' personal financial management practices vary over time?
3. How can financial education influence (a) identification with personal financial management and (b) personal financial management practices?

The project consisted of a survey designed to examine the impact of a financial capability education course provided to students in England aged 16-18. The participating students were part of an optional module, which was offered at schools across the UK who opted to provide the module.

The FLE project comprised a three-year longitudinal survey that began in September 2004 and was conducted in the UK on behalf of the Institute of Financial Services—IFS School of Finance which is a recognized qualification award organization and called the London Institute of Banking & Finance now. The IFS School of Finance offers a number of financial capability qualifications for 14-19 years old, and the programs have been extended to undergraduate, master and continuing professional development levels. Indeed, the introduction in 2004/5 of the project was made at the IFS School of Finance in order to evaluate their Certificate in Financial Studies (CeFS) which provided a unique opportunity to examine the impact of a substantial one-year course in financial literacy. CeFS is an "AS level" qualification, which carries credit that can be used for university entrance, usually comprising one of a number of similar status qualifications studied before moving on to university or other Higher Education Institution. Many of the students were also taking a business studies course, such as "A" Level Business Studies (an academic route qualification) or an equivalent: vocational track course in Business (e.g. BTEC or AVCE). In the UK, these are known as level 3 courses. Level 3 is taken mainly by 16-19 year olds at the pre-university stage. However, this financial studies course was not exclusively for Business students, and drew students across the full range of subjects. The trajectories or stories of the students began prior to university but during the course of the three years most moved on to university or sometimes to work. It can be viewed as a use of financial studies course in which there is an emphasis on application and students' own personal financial management.

There are concerns internationally about low levels of financial capability among the general population (AdFLAG, 2000; FSA, 2006; Huston, 2015; OECD, 2005). In Britain, the Financial Services Authority (2006) points out the pressing need to equip those under 40 years old with greater financial capability. Politicians and employers have called for educational programs that provide young people with the knowledge, skills and attitudes they need to be able to make informed financial decisions throughout their lives. According to Lord (2001, p.1), financial literacy is an "essential requirement" for every consumer in the 21st century market, rather than a "desirable trait". In the FLE project, the CeFS course is taken mainly by sixteen to eighteen year olds. The 6th Form College in the UK represents the last stage of the secondary school (high school) where students (16-19 years old) aim to prepare for their A Level or equivalent examinations in England, Northern Ireland and Wales. In the England, the compulsory education is finished by the end of year 13. After that, students can either stay at secondary school attached with a 6th form or vocational college. Drawing on this longitudinal hybrid design, the FLE tracked 2000 + 6th Form College, school and FE students over the time they participated in the IFS School of Finance Certificate in Financial Studies - CeFS.

Financial literacy is also mediated by many social differences, which has been well documented in the literature, with gender and ethnicity having particular prominence (Chen & Volpe, 1998; Chen & Volpe, 2002; Hayhoe, Leach, Tuner, Bruin, & Lawerence, 2000; Volpe, Chen, & Pavlicko, 1996). Hence, it is especially important to examine social differences such as ethnicity and gender within an analysis of attitudes, dispositions and practices in contexts of educational research. The existing literature shows students' personal financial management practices and related aspirations vary with social categories, such as gender, ethnicity and social class (Chen & Volpe, 1998; Chen & Volpe, 2002; Hayhoe, Leach, Turner, Bruin, & Lawerence, 2000; Ozgen & Bayoglu, 2005; Roy Morgan Research, 2003; Volpe, Chen, & Pavlicko, 1996). Other literature informs us that the range of financial products purchased varies with socio-economic status; for example, people on low incomes make little use of bank accounts for day-to-day money management (Collard, Kempson, & Dominy, 2003; Henager & Cude, 2016) and have specific attitudes toward home credit (Brooker & Whyley, 2005). Additionally, other background characteristics affecting financial literacy include educational background, work-experience, age, and personal income (Chen & Volpe, 1998; Davis & Durband, 2008). The modeling of change in this study of learning in a financial literacy course will consider these factors as well.

As the need for improving financial literacy has gained currency, many have begun to raise the questions – will education improve young people's knowledge about finance and will that knowledge "translate into more effective consumer behaviors (Mandell & Klein, 2009, p. 9; Tennyson & Nguyen, 2001, p242)?". However, empirical research on the impact of financial education has been rather scarce, as Braunstein and Welch (2002) suggest is due to the challenges of quantifying the influence of such programs. In particular, there has been a cautious approach to the development of statistical techniques in the field and new innovative approaches are very much needed. Indeed, we found that there was a distinct paucity of appropriately validated measurement tools available, and where tools did exist there were problems in contextual transferability. It is often the case in educational or other social research that attitudinal measures or measures of other dispositions are not available and that development of these may go on alongside existing work.

Our response to the issues of quantifying measures was twofold. Firstly, we were in a position to design and pilot two measures of financial capability using Rasch Measurement (Bond &

Fox, 2001), which we report elsewhere; Pampaka, et al. (2009) developed measures of financial knowledge and perceived self-efficacy using Rasch modeling techniques. However, the validation of such measures takes time and it is often the case in educational research that funders demand early results and that answers to important social problems are required in the context of a general underdevelopment of appropriate social research measurement tools. We needed to find a way to model change based on single item response variables. We also needed to find valid ways to investigate course impact, which could rely on single ordered categorical or unordered categorical items. We make no claims to be measuring latent dimensions or characteristics, and so we limit our conclusions to the items concerned rather than using them as sets of proxy indicators for latent traits such as confidence or enjoyment. The FLE study drew on a variety of research methods and used a large-scale questionnaire survey, case studies, and follow-up interviews, providing a rich base of data for analysis. In this paper, we develop an alternative quantitative method to measure the change over time in financial literacy in the UK. Then we illustrate the quantitative method developed here to model change over the study period for the FLE project.

Secondly, another major advantage of the method developed in this paper is the capability of measuring the future events given the event's current status. For this, we have applied the Monte Carlo simulation method for sampling the population in order to then make predictions. Our decision to apply the Monte Carlo simulation method goes back to an earlier analysis, which measured changes in students' perceptions towards personal financial management, which we come back later in the paper. We found this method helpful as a means to understand the particular behavior we saw reflected in the data, however, it did allow for measuring predictions of future events, which we propose, will be of particular interest to those concerned with curriculum development. In this paper, the Monte Carlo simulation method for generating the population from samples seemed to offer distinct possibilities for developing an alternative way to model changes in responses over time given the current status (e.g. ages, gender, and social background) and social characteristics of a sample.

We suggest that the quantitative model presented in this paper will be of wide interest to those in educational research, and indeed, more widely in areas of applied social sciences. This is an approach that we believe to the best of our knowledge, is new within educational research and has appeal both in its simplicity and utility. Given a distinct lack of validated quantitative measures in the field, practitioners often need to work with single item data. Applying this model offers a practical way forward for some of the problems we face in the field. Davis, et al. (2006) drew on this to develop a decision model method to examine changes over time in responses to single item ordered categorical data between gender groups.

The following section of this paper will explain how we develop the method of modeling the change in responses over time in general. The data resource used for illustrating the new method developed is described in the following section. In the section following that, the method developed in this paper will be demonstrated through measuring change in the reported financial practices and beliefs of students who were enrolled in a course in personal finance in 6th form and further education (FE) colleges across the UK. In our concluding section, we comment on the advantages and challenges of this probabilistic model and indicate the extensions of the method in the future.

New Model for Changes of Attitude

The objective of modeling changes in attitude is to examine if an activity, such as a training course, will produce changes over time. In this approach, it is assumed that change will be reflected by a difference in the responses given to the same question (item) over the training course. The ideal way of estimating changes in attitudes is to compute the probability of the response to a question at each time point. Change would mean that the difference of the probabilities would change over time. If a question has multiple levels of response (more than two levels), changes over time would be seen in the switching between responses at each time point and there would also be a number of the possible switching patterns. For example, a question (item), *j*, of a subject, *i*, contains three possible outcomes, e.g. Yes, Don't know, and No (see Table 1 below). Table 1 illustrates that there are three switching patterns of a response between two time points, *s* (study's early period) and *t* (study's later period). The three patterns in this study are defined as: 1) a shift from non-positive response in time *s* to a positive response in time *t* named as positive change, 2) a shift from a positive response in time *s* to a non-positive response in time *t* named as negative change, and 3) no shifting on the response over the time named as no change. The method developed in this paper takes into account the response with multiple levels, since the question (item) with multiple responses is very common in this kind of study on attitudes.

Therefore, the positive change (+) of question *j* for subject *i* between time *s* and time *t* can be presented as

$$ {}_{+}C_{ijst} = \left(Y_{ijt} \cap DK_{ijs}\right) \cup (Y_{ijt} \cap N_{ijs}) \cup (DK_{ijt} \cap N_{ijs}) \quad (1) $$

Correspondingly, the negative change (-) of the question over the same period is described as

$$ {}_{-}C_{ijst} = (DK_{ijt} \cap Y_{ijs}) \cup (N_{ijt} \cap Y_{ijs}) \cup (N_{ijt} \cap DK_{ijs}) \quad (2) $$

If a response to a question is binary, for example Yes and No, positive change is a shift from negative response at time *s* to a positive response at time *t* while negative change is a shift from a positive response at time *s* to a negative answer at time *t*. Simply, changes of the binary response would be ${}_{+}C_{ijst} = Y_{ijt} \cap N_{ijs}$ and ${}_{-}C_{ijst} = Y_{ijs} \cap N_{ijt}$, positive and negative respectively. Davis, et al. (2006) computed the changes of a response over time based on outputs of cross tabulations for the binary response in the financial literacy education study. In their analysis, the change in attitude on personal finance management was estimated as the difference between the proportion of positive changes and the proportion of negative changes from one survey to another survey, for example from survey A to survey B. In particular, the approach used in that paper can only be applied when responses at both time points have been observed. However, the application of modeling changes is to assist the future decision-making or management in practice, for example, to help the educator to monitor the transition between the outcomes of the repeated questions over the period of the teaching practice in order to improve the performance of teaching and learning. In this paper, we consider the method that is able to directly model changes of attitude given the predicted response of the repeated question in a longitudinal study. This method uses a simulation approach to predict the future responses for the population given current responses for the same question. The change we represent is therefore from a current status to a predicted time in the future. Let responses of a repeated question *j* of subject *i* be $Z_{ijr}, Z_{ijs}, Z_{ijt}$ and a vector of predictors be $X_{ijr}, X_{ijs}, X_{ijt}$ at time r, s, t ($r < s < t$). In order to proceed with the modeling work, we will first predict the responses to the same questions given the covariates, e.g. employment, education, and exam mark (equation 3). This modeling also considers the impact of the previous responses, say, Z_{ijr} and Z_{ijs} regarding the question on the future outcome (Z_{ijt}) of the repeated question (equation 3). The probabilities of the response of a repeated question *j* of subject *i* at time *t*, $P(Z_{ijt})$, will be given by

$$P(Z_{ijt}) = f(X_{ijr}, X_{ijs}, X_{ijt}, Z_{ijr}, Z_{ijs}) \quad (3)$$

With this model (equation 3), an overall change in responses from time point *s* and time point t, C_{ijst}, is defined as:

$$prob(C_{ijst}) = prob({}_{+}C_{ijst}) - prob({}_{-}C_{ijst}) \quad (4)$$

For a binary response, $prob(C_{ijst})$ is computed straightforwardly. Responses were grouped into a binary category if they were in the form of categorical data with more than two levels. In these cases, the probability of change (C_{ijst}) has been counted by taking the average of all possible grouping responses. The formula is defined as:

$$prob(C_{ijst}) = \frac{\left(prob(C_{ijst,1}) + prob(C_{ijst,2}) \ldots + prob(C_{ijst,n})\right)}{n}$$

where $k = 1,2,\ldots,n$ denotes the possible grouping of responses. The purpose of using this method was to minimize the risk of losing grouping information.

The method of modeling changes of attitude over the time in this paper requires a probabilistic model for predicting the responses for population samples. Thus, we need to specify a class of models and a set of potential predictor variables in order to proceed with equation 3. To simplify this prediction problem, we assume that the responses to questions are independent given the values of the predictors in the prediction model. We can then use a univariate generalized linear model, because responses are observed directly as categorical response.

Logistic regression models the logit transformation of the observed event's probability as a linear function of the explanatory variables (Hosmer & Lemeshow, 1989). If the categorical response variable is ordered, the ordinal model assumes that

$$logit(prob(Z \leq k)) = \alpha_l + \beta^T X \text{ for } k = 1,...,n-1$$

where the response variable Z is measured in one of *k* different categories, α_l are *n-1* intercept parameters, β is the slope parameter vector, and $X = (x_1,x_2,x_3 \ldots..)$ is a vector of covariates. The ordered model fits a cumulative model, which we assume in this study is a parallel line's regression model based on the cumulative probabilities of the response categories. The response Z is modeled as

$$\begin{array}{l}
if\ \beta^T X < c_1 + \varepsilon \quad \text{simulated results} = \text{Respons1} \\
if\ c_1 + \varepsilon < \beta^T X < c_2 + \varepsilon \quad \text{simulated results} = \text{Respons2} \\
if\ c_2 + \varepsilon < \beta^T X < c_3 + \varepsilon \quad \text{simulated results} = \text{Respons3} \\
\qquad\qquad \text{M} \\
\qquad\qquad \text{M} \\
if\ \beta^T X > c_k + \varepsilon \quad \text{simulated results} = \text{Responsk}
\end{array}$$

where $\beta^T X$ is the linear predictor, $c_1 + \varepsilon$ and $c_{-1} + \varepsilon$ are a random cut-off point for winning and losing with a systematic component c and a random component $\varepsilon \sim N(0,\sigma^2)$. Therefore, the categorical response Y with three levels $(p_1, p_2, p_3$, where $p_1 + p_2 + p_3 = 1)$ is given by

$$p_1 = \Phi(-c_1 + \beta^T X)$$

$$p_0 = \Phi(-c_1 + \beta^T X) - \Phi(-c_{-1} + \beta^T X)$$

$$p_{-1} = 1 - \Phi(-c_1 + \beta^T X)$$

with the cumulative distribution function of the standard Normal distribution $\Phi(\cdot)$. It is necessary that $c_{-1} < 0 < c_1$ and $X = (x_1, x_2, x_3 \ldots..)$ is a vector of covariates. This model can be contrasted with the ordinal logistic regression model for which

$$p_1 = \text{logit}^{-1}(\alpha_1 + \beta^T X)$$

$$p_2 = 1 - \text{logit}^{-1}(\alpha_1 + \beta^T X) - \text{logit}^{-1}(\alpha_3 - \beta^T X)$$

$$p_3 = \text{logit}^{-1}(\alpha_3 - \beta^T X)$$

where $\text{logit}^{-1} : \Re \to (0,1)$ such that $\text{logit}^{-1}(x) = \exp(x)/\{1 + \exp(x)\}$. This is sometimes referred to as the proportional-odds model (McCullagh & Nelder, 1999, p.154). The proportional-odds model is one of ordinal logistic regression model based on the cumulative response probabilities.

However, the proportional-odds model assumes that the odds ratio is not systematically increasing as systematically decreasing in *k*. In the other words, β is independent of the choice of category *k*. In addition, the ordinal logistic regression model is known as the partial proportional odds model. The proportional odds model releases the constraint that ordinal logistic regression assumes there is no difference between the impacts of covariates on the probabilities of the different outcomes. The proportional odds model loses the information of ordering of outcomes. Ordinal probit regression is obtained by replacing $\text{logit}^{-1}(.)$ in the above equations with the cumulative distribution function of the standard normal distribution, $\Phi(.)$. The probabilities of different responses are calculated from the prediction model and a uniform random number called α is simulated.

Data Resource

Our research involved a sample of ninety-nine schools. The survey study aims to explore how the financial literacy education influences students' attitudes/aspirations towards personal financial management and future careers in financial sectors. Our survey design and analysis allowed us to model how students changed their attitudes/opinions on a particular item given their previous responses and other information over the financial literacy education course.

The FEL project designs a longitudinal survey, which combined a repeated questionnaire survey and in-depth qualitative interviews with students in clusters of case study institutions. Eleven surveys were introduced to students who study the CeFS course over 3 cohorts in Figure 1. We followed 3 cohorts of students (2004/5, 2005/6, and 2006/7) over a period of up to three years, with the questionnaire data for each cohort being collected at the beginning (as near as was feasible) and at the end of the course. Figure 1 also shows that the cohorts were followed up with a postal questionnaire, six months (first 2 cohorts) and eighteen months (the 1st cohort) after the completion of the course. Its strengths were that data was collected for a high proportion of the population of students taking CeFS and repeated data allowed for a comparison between time-points.

The survey designed in the project mainly contains five parts, which consist of: "Confidence in financial matters, Attitudes to money, Aspirations, Personal Finances, and Background information". This paper focuses on one example of the use of the developed model with respect to changes in career aspirations, among a group (numbers of individual responses to items vary from 356 to 758) sampled from a population of 1,205 students on a one-year part-time course (typically 4 hours a week contact time) in CeFS studies. These questionnaires with this item were distributed in the first two cohorts (2004/5, 2005/6) of the project, which at this stage provided a total of three surveys for the analysis in this paper. These consist of two follow-up surveys, which were distributed to the students in cohort 1 (S_{14} and S_{15}), and one survey that was distributed to cohort 2 (S_{23}) immediately after they completed their final compulsory examination. The specific question used to illustrate this analysis is:

How likely are you to consider a career in the financial services sector?

A. Very likely
B. Likely
C. Unlikely
D. Very unlikely
E. Already work in the financial services sector
F. Undecided

The Application of the Model in Financial Literature Education

Let Z_{FCT} denote the response to the item/question (C) of considering a career in the Financial Services sector within the subject of financial literacy education (F) at time T (using the order of the survey as the time line, e.g. T represents the time of the survey distributed to the students, say S_{14}, S_{15} and S_{23} in figure 1). This question was common to all questionnaires. The frequency distribution is listed in table 2 for this question grouping by gender at time T. Table 2 shows that just over half (very likely or likely responses) of students were considering a career in FS sector when surveyed 6 months after course completion. Finding gender differences in the responses was typical across the surveys, although, as in this example, the difference was sometimes small despite the statistical significance. However, table 3 implies that there is no difference between gender on medians and standard deviations (assuming the participants who are already working in the financial services sector will likely keep the career over the study period).

Now we consider the specification of suitable predictor variables. We need to model the relationship between responses and information, such as the type of school, gender, and ages. The responses of the cohort 1 (2004/5) are set as training data for model fitting, and the responses of the cohort 2 (2005/6) are reserved for examining the model fit. It is worth noting that other covariates were considered in the model fitting but were found to be inessential in terms of the Akaike Information Criterion (AIC).

In this study, the independent variable, x_{wh}, is $X_{wh} = c(x_{w1}, x_{w2}, .. x_{wr} ., x_{ws}, x_{wt})$ where w, say gender (G), when presenting indicates a particular predictor and $h(h \in (1,2,r,..,s,..,t))$ represents a particular survey in the cohort. In particular, X_{wh} also could be Z_r or Z_s (previous response of the same question), but not Z_t ($r < s < t$).

The subset of fitted models is presented in table 4. The best models are selected from 1,640 subset models in terms of minimum AIC values. Table 4 shows that the covariance selected in the best model is based on responses to the same question in the earlier surveys. The minimum value of AIC (145.416) in subsets of models shows that the estimations using the ordinal model are better than those using the nominal model. It also indicates that the $x_{S_{14}}$ ($Z_{S_{14}}$) and the $x_{S_{15}}$ ($Z_{S_{15}}$) can explain the responses in follow-up surveys better than other variables in this study and their relationship is statistically significant. We then measured changes to responses over time based on the predicted responses in the follow-up survey (S_{23}) in cohort 2.

The parameters estimated of the best model are presented in table 5. The p-values of these variables indicate that these independent variables are statistically significant to the responses of the question about aspiration in career. Both nominal and ordinal logistic regression models were fitted to the data. The responses of aspiration in career in the follow-up survey, S_{23}, were closely related to the corresponding response in the 4th and 5th surveys in cohort 1. However, the nominal model in table 4 shows that a multinomial logistic regression model was not suitable for this data.

Given the parameters estimated using the equation 3 in table 5, we first compute the probability of $P(Z_{FCS_{23}})$ for each response. Then applying for the equations 1 and 2, we calculate both $_{+}C_{FCS_{15}S_{23}}$ and $_{-}C_{FCS_{15}S_{23}}$ for each response of the question (careers in financial services). Then the overall probabilities of changes for the individual response have been worked out using equation 4. The estimated changes of responses over time given the current responses in career are listed based on 100 iterations in table 6 using the program of Visual Basic Application.

The overall change (34.366) shows the change in students' attitudes of considering a career in the financial sector following the course. However, the changes across the levels of categories are consistent due to the light difference of $prob(C_{FCS_{15}S_{23}})$ (34.308, 34.405). It possibly explains that the change on the individual has a similar pattern or trend. All of changes over time for this question are positive. It implies that studying the financial services course has increased students' aspirations towards a financial services career. The greatest change for this item over time is from "very likely" to "already work in the financial services sector" by 34.366, which is highlighted in table 6. Table 6 provides illustration that the method developed in this paper is able to directly compute the exact changes over time and the efforts of covariates on the response. However, neither of them can report the amount of the transition between the time period and the impacts of studying the CeFS course.

Conclusion

The contribution of this paper is twofold. First, it develops a new method for modeling the changes of categorical responses over time for the longitudinal survey data. Comparing the previous research on modeling the changes in students' responses to particular items, our method employs Monte Carlo simulation techniques to generate the population. The method is illustrated using longitudinal survey data on students who were studying a course in personal financial management in the UK.

Second, it provides a decision model for modeling the longitudinal time point changes on the personal finance attitude and behaviors. We showed how changes over time could be computed based on the "positive/negative" responses of survey items, calculating the proportion of changes over time for background variables during the course using a sample of surveys from the IFS School of Finance in the UK.

In general, this method will be useful for generating patterns of change in perceptions in various fields of applied social science. Indeed, in the future, the covariance of the prediction model could be updated based on the relationships across questionnaire survey items. From the aspects of Bayes Theorem, we can assume the categorical responses follow a common statistical distribution and combine the Bayesian inference and logistic regression model for this measurement. This is demonstrated using the item on career choice.

For the same item, the model indicates the importance of its prior response on posterior response. Educationally, this is interesting because it suggests that aspirations are set early on and hence social differences have been subsumed within the predictor variable $Z_{S_{14}}$, and in the case of our study prior to course selection on entering post-compulsory education. This demonstrates face validity, given that many of the students were taking a vocational program in business studies. It also suggests that interest in the topic has an add on effect in terms of learning trajectories, with those who are studying the topic for career reasons more likely to progress in their learning about the topic.

Our research used a hybrid design and our interview data suggests that what may be happening is that students had often already decided on a broad career prior to their involvement in the course and our research project. For example, students may choose business or technology careers when their A Level or BTEC in programs choices are made. Qualitatively, we also noted course impact was related to a prior expressed interest in business, more specifically an interest in business finance or financial studies.

Furthermore, our narrative analysis of the students' educational biography data confirmed existing career and degree subject patterns are influenced in complex ways by sociocultural factors, especially ethnicity, gender, and social class. For example, sociocultural differences manifest in structurally different ways to suggest a deeply cultural production of the self (Kalambouka, et al., 2012). This means that existing patterns of behavior concerning career choice are not easy to change through educational provisions. We suggest that it is therefore of interest to policy makers to understand better the interplay between career choices and engagement in learning that is provided by the 14-19 years old curriculum.

The method developed in this paper mostly considers the response variable, which is categorical. This is due to the orientation of the study for survey analysis. In the case that the outcome of the item is continuous, the method developed here has to be slightly adjusted. For example, the equation 3 can be produced using a generalized linear model or other statistical model, which is suitable for continuous dependent variables. In terms of the calculation of change, there are two ways to deal with this. The first possible approach is to cluster the continuous responses into a number of groups and index those groups as categorical variables. The equations 1 and 2 are still applicable. Another way is to calculate the change for each possible response over the time for the numerical response item.

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Table 1 An Example of Switching Patterns of Three Responses at Two Time Positions.

Responses		*T*		
		Yes (Y)	Don”t Know (DK)	No (N)
s	Yes (Y)	~	-	-
	Don”t Know (DK)	+	~	-
	No (N)	+	+	~

Note: + Presents Positive change, - presents negative change and ~ presents no change.

Table 2 2004/5 Summary of Considering A Career in FS Sector by Gender.

S_{14} Q_{12a}: Career in financial sector		Gender		Total
		Female	Male	
Very likely	Count	18	37	55
	% within Gender	18.182	27.407	23.504
Likely	Count	32	34	66
	% within Gender	32.323	25.185	28.205
Unlikely	Count	15	22	37
	% within Gender	15.152	16.296	15.812
Very unlikely	Count	10	13	23
	% within Gender	10.101	9.630	9.829
Already work in the financial services sector	Count	5	3	8
	% within Gender	5.051	2.222	3.419
Undecided	Count	19	26	45
	% within Gender	19.192	19.259	19.231
Total	Count	99	135	234
	% within Gender	100.000	100.000	100.000

Table 3 2004/05 Statistics of Considering A Career in FS Sector.

$S_{14}Q_{12a}$: Career in financial sector	n	Median	Variance	Standard Deviation	Interquartile Range	Skewness	Kurtosis
	234	2	3.202	1.789	2	0.616	-0.990
Female	99	2	3.104	1.762	2	0.579	-1.041
Male	135	2	3.284	1.812	3	0.658	-0.938

Notes: 2=”likely”.

Table 4 2004/05 Results of Model Fitting: Log-likelihood and AIC for Various Models (Subset of Those Fitted) for Declared Career Choice.

Predictors	Number of parameters	Log-Likelihood	AIC
$x_{S_{14}} + x_{S_{15}}$	7	-65.708	145.416
$x_{S_{14}} + x_{S_{15}} + gender + ages + schooltype + ethnic$	11	-64.682	151.364
$x_{S_{14}} + x_{S_{15}} + gender + ages + schooltype$	10	-64.704	149.408
$x_{S_{14}} + x_{S_{15}} + ages + schooltype$	9	-64.743	147.486
$x_{S_{14}} + x_{S_{15}} + schooltype$	8	-65.525	147.050
$x_{S_{14}} + x_{S_{15}} + ages * gender$	8	-65.136	146.272
$x_{S_{14}} + x_{S_{15}}$ (nominal)	15	-68.502	167.004

Table 5 2004/05 Fitted Parameter Estimates of Aspiration in Career for Minimum AIC Logistic Regression Model (Ordinal) with the Covariates $x_{S_{14}}$ and $x_{S_{15}}$, with Standard Errors and P-values (Observed Significance Level of Test of Parameter Value Equals Zero).

Outcomes	Coefficient	Standard Error	Z-values	P>|z|	95% Confident Interval	
β_1	0.728	0.327	2.230	0.026	0.087	1.370
β_2	0.866	0.337	2.570	0.010	0.206	1.527
α_1	1.034	1.048				
α_2	4.210	0.988				
α_3	5.584	1.130	(Ancillary parameters)			
α_4	6.764	1.267				
α_5	9.423	1.554				

Table 6 2004/05 and 2005/06 The Changes of Responses Over Time for Intended Career Choice.

Responses	$prob({}_{+}C_{FCS_{15}S_{23}})$	$prob({}_{-}C_{FCS_{15}S_{23}})$	$prob(C_{FCS_{15}S_{23}})$
m=1	**96.125**	61.742	34.383
m=2	96.105	**61.700**	34.405
m=3	96.103	61.762	34.342
m=4	96.105	61.733	34.372
m=5	96.038	61.730	34.308
m=6	96.100	61.717	34.383
Overall	96.096	61.731	34.366

Notes: m=1 presents already work in the financial services sector; 2 presents very likely; 3 presents likely; 4 undecided; 5 presents unlikely; 6 presents very unlikely.

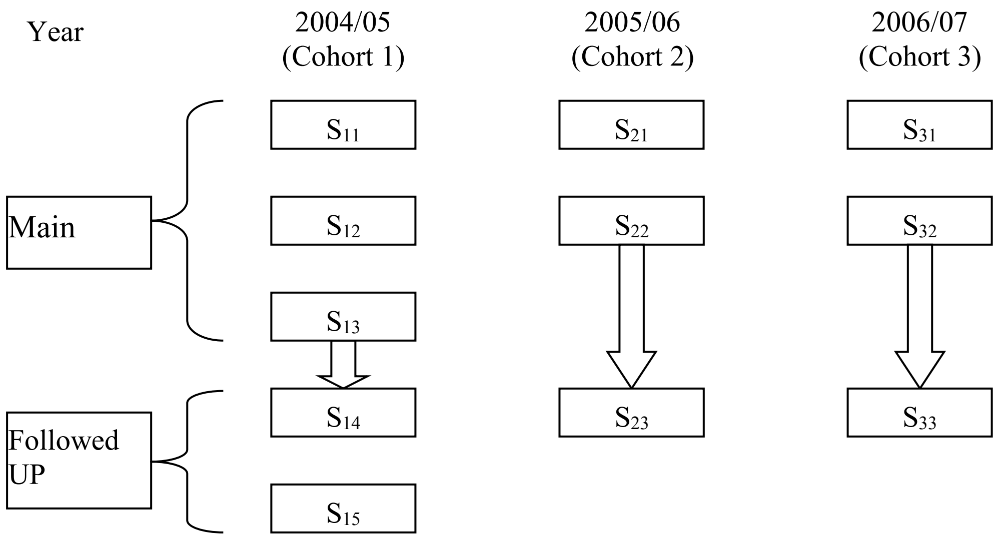

Figure 1. **The distribution of questionnaires over study period.**